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Short communication

Investigation of nickel–metal hydride battery sorting based on charging thermal behavior

Kaizheng Fang, Shi Chen, Daobin Mu*, Borong Wu, Feng Wu

Beijing Key Laboratory of Environmental Science and Engineering, School of Chemical Engineering and Environment, Beijing Institute of Technology, Beijing 100081, China

HIGHLIGHTS

► Ni–MH battery sorting is investigated based on charging thermal behavior.
► An SOM model is constructed to conduct the sorting work.
► Batteries are effectively sorted into three categories by the model.
► Batteries sorted in each category can keep consistency in thermal behavior and discharge performance.

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ABSTRACT

In this study, the sorting of nickel–metal hydride batteries is investigated based on their charging thermal behavior. A self-organization map (SOM) model affiliated to artificial neural network is constructed to conduct the sorting work. The sorting principle is described in detail to support the model. A batch of batteries is charged in various rates to collect training data closely related to battery thermal behavior. It is indicated that the model can master the regulation of sorting well after training. As a result, the batteries are classified by the SOM model into three categories of high heat generation battery, middle heat generation battery, and low heat generation battery, which corresponds well with the training result. The model thus allows the batteries in the same category to be selected for the consistency in thermal behavior as well as discharge performance.

1. Introduction

Currently, a major limitation to the application of secondary batteries in electric vehicles is the battery safety which is intimately associated with the heat generated during charging/discharging process. Therefore, as one of key features, the thermal issues have being paid on attentions for Ni–MH and lithium-ion power batteries. The thermal behavior of the batteries are also investigated extensively from various aspects, but, it is still of special concern owing to its crucial role in battery safety. Sato and Yagi [1,2] studied the contribution extent of each heat factor to the total heat generation during charging/discharging. Kim et al. [3] proposed a three-dimensional thermal abuse model for Li-ion battery and demonstrated multi-dimensional behavior of thermally abused battery. These studies primarily focused on the thermal behavior of a single battery through modeling analysis. Also, some work was done on the thermal management of batteries to enhance the safety in their application, such as the thermal model constructed by Mahamud and Park [4] to improve temperature uniformity. We reported a model based on artificial neural network to predict the surface temperature of Ni–MH battery during charging, with the aim of guaranteeing the thermal safety of a single battery [5]. In addition, it is worthwhile to note the thermal runaway occurring in a group of batteries due to their thermal inconsistency. For the safe use of power batteries, it should be an effective approach to pre-sort the batteries for maintaining their performance consistency in a group. But, the sorting work is usually complicated with detailed analysis on the electrochemical performance of the batteries. In an attempt to make battery sorting simple, we found it is possible to perform sorting using the difference in the thermal behavior of batteries, however, no results were reported thus so far on this aspect. Therefore, in this work efforts were made to investigate Ni–MH

* Corresponding author. Tel.: +86 (0)10 68918770; fax: +86 (0)10 68918828.
E-mail address: mudb@bit.edu.cn (D. Mu).

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battery sorting based on charging thermal behavior. The sorting procedure was conducted with the help of an artificial neural network model of Self-organization Map (SOM). The discharging performance of the sorted battery was discussed as well.

2. Battery sorting principle

The surface temperature of Ni–MH battery will rise due to various kinds of heat generated during charging process [1]. While the total heat is different for each individual battery, so the surface temperature of the battery differs from each other in a battery group upon working. It is supposed that, the more quantity of the heat is generated, the higher the surface temperature of the battery becomes under the same charging conditions. Based on the heat quantity, the batteries are classified into three categories in this study, briefly termed as high heat generation battery (HHB), middle heat generation battery (MHB), and low heat generation battery (LHB). Taking safety into account, it is expected to keep the thermal consistency of batteries in the same category as much as possible by pre-sorting. Here, an SOM model was employed to satisfy this purpose.

SOM, which can map data from high dimension to low dimension through the working of neurons in the model, is often applied to solve pattern recognition and classification [6]. It is a feed forward neural network adopting an unsupervised learning algorithm, and can systematize similar vectors by capturing the topology and distribution of all the vectors input to it [7]. The SOM model constructed for battery sorting is schematically shown in Fig. 1. Here, $p_{i=1,2,3}$ mean model's input vectors whose numbers are three for each battery, corresponding to the battery surface temperatures at the end of charging in three different rates. Each input vector has a weight vector (w_i) connected to it. u is a bias vector with constant value. The neurons in the hidden layer perform the classifying work, their numbers are set as three because of the three categories presented above. a, b and c represent three neurons corresponding to output categories I, II, III, respectively. The recognition process will be described in detail in following sections.

In order to determine the assignment of each battery, the neurons in the SOM model need to participate in competition to produce a winner recognizing the input vectors of the battery [8]. The competition process is conducted through comparing the similarity which is judged by an average value of Euclidean distances between the neuron's weight vectors and the battery's input vectors [9]. The smaller the value, the more similar these two groups of vectors are. The Euclidean distance is calculated by equation (1),

$$\|w_i - p_i\| = \sqrt{(w_i - p_i)^T (w_i - p_i)} \tag{1}$$

When the average Euclidean distance between one neuron's weight vectors and one battery's input vectors is smaller than those between other neurons and the same battery, the neuron will become the winner that can recognize the battery. If the neuron recognizes a number of similar batteries, its weight vectors need be trained to approach the input vectors of each battery for ensuring a minimum difference between themselves and the input values [10]. Then the neuron can classify the whole similar batteries as one category. The algorithm to train the neuron's weight vectors is expressed in equation (2) [9],

$$\Delta w_i = lr \cdot (p_i - w_i) \qquad [2]$$

where lr represents learning rate. Following the same training procedure, other neurons are also trained to achieve the optimum recognitions. Thus, all the batteries can be classified successfully.

Moreover, every neuron will memorize the classification patterns obtained by the training. Therefore, a neuron can recognize the input vectors of a similar battery else input to the model. If a dissimilar battery is encountered, the neuron may not recognize it owing to the failure in the competition with another neuron. The new winner will classify the battery as another category. As a result, the SOM model sorts out all input vectors based on the computing recognization.

3. Experiments

A batch of 8 Ah cylindrical Ni–MH batteries (No. B1–B12) was used in experiments. The mean voltage was around 1.25 ± 0.01 V for each battery (1 C discharging). The battery was put into a high–low temperature testing chamber for its testing at a constant temperature of 25 °C. The battery was charged from its SOC of 0 in the rates of 1 C, 5 C, and 8 C to its SOC of 110%, 110% and 100%, respectively. An infrared thermal imager (VarioCAM hr from German Infra Tec Company) was used to record the surface temperature of the battery during charging.

The SOM model was constructed on a MATLAB software platform.

4. Results and discussion

It is feasible to determine the maximum value of battery surface temperatures from the infrared image. For example, point P1 in Fig. 2 indicates the maximum temperature appearing on the surface of B1 at the end of 1 C charging. Fig. 3 shows the maximum value of battery surface temperature (abbreviated as BST_{max}) at the end of charging. BST_{max} differs from each battery regardless of charging rates (1 C, 5 C, or 8 C). This indicates that different thermal behavior exists amongst the batteries during charging, which may cause heat unbalance in a group of batteries. BST_{max} is thus an important feature reflecting the thermal behavior of the battery; therefore, battery sorting is performed using the data of BST_{max} as input variable for the constructed SOM model.

When the variables are input to the model, the neurons are trained to recognize them. The training result of B1–B10 is shown

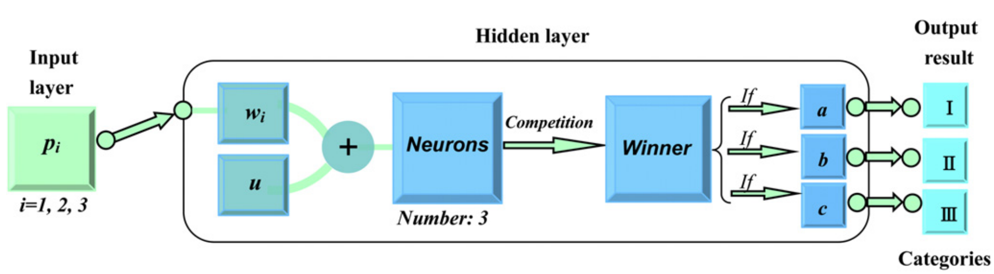

Fig. 1. The structure scheme of the SOM model used in sorting.

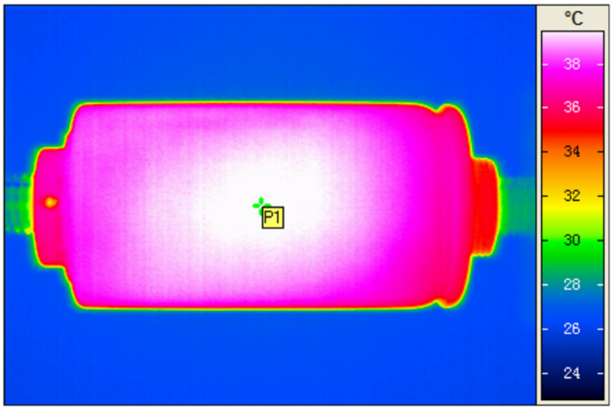

Fig. 2. The infrared image of B1 at the end of 1 C charging.

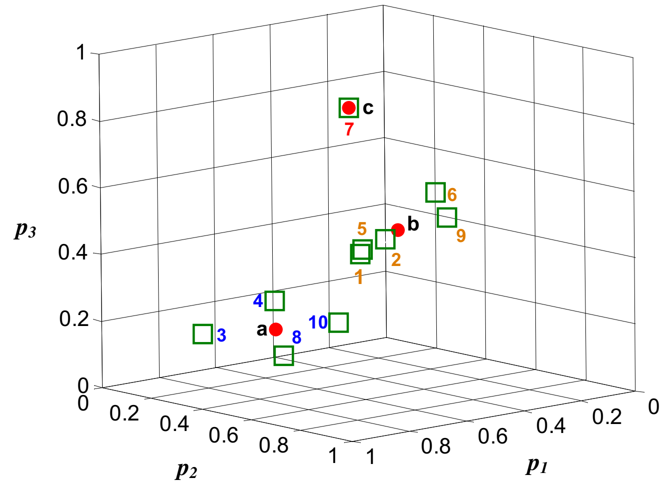

Fig. 4. The model's training result with the data of B1–B10.

in Fig. 4. The three axes p_1, p_2, and p_3 correspond to the normalized BST_{max} data obtained under 1 C, 5 C, and 8 C charging, respectively. '□' indicates battery, and solid circles '●' a, b, and c represent three neurons. It can be seen that neuron '*a*' is located near B3, B4, B8, and B10; neuron '*b*' is near B1, B2, B5, B6, and B9; and the location of neuron '*c*' is the same as that of B7. The respective average Euclidean distances between neuron '*a*' and B3, B4, B8, B10 are all smaller compared to the ones between '*a*' and other batteries. Therefore neuron '*a*' recognizes the four batteries as the same category. Likewise, neuron '*b*' recognizes B1, B2, B5, B6, and B9 as another category, while B7 belongs to a third category. Further, the output result of the model is shown in Fig. 5. Here, ten batteries are classified into three categories I, II, III, responding to the above-mentioned LHB, MHB, HHB, respectively. B3, B4, B8, and B10 belong to LHB; B1, B2, B5, B6, and B9 are sorted as MHB; and B7 is sorted as HHB. It is indicated that the sorting result is based on the training outcome of the neurons, and each neuron represents one category of batteries. Using this model, the batteries are sorted into three categories, in each one of which the batteries are estimated to have similar thermal behavior.

Because the model has mastered the regulation of battery sorting, even the input variables are just provided by a single battery, it now should be possible to determine which category the battery would be sorted into. When vectors of a new battery are input to the model, the average Euclidean distance is calculated between each neuron's weight vectors and the input vectors to obtain a winning neuron. The winner will respond to the battery, and classify it. Accordingly, when the data of B11 are input to the model as new vectors, neuron '*b*' will recognize them, and sort B11 as MHB. When the data of B12 are input to the model, neuron '*a*' will respond to them and classify B12 as LHB. In a word, B11 fits the case of II, and B12 falls into category I. Therefore, the SOM model is able to not only classify a group of batteries, but also sort a single battery.

Five batteries (B5, B7, B8, B9 and B10) are selected to analyze their BST_{max} change curves during a whole charging process. B7, B5 and B9, B8 and B10 belong to HHB, MHB, LHB, respectively. The curves in various rates of charging are shown in Figs. 6–8. Each curve consists of a slow-rising temperature section (SRS) and a fast-rising section (FRS) [11]. The temperature rise rate of FRS is much higher than that of SRS due to the contribution of combination heat [1], which significantly influences BST_{max} at the end of charging. When charged in 1 C, the transit time of B7 from SRS to FRS starts earlier than that of the other fours, leading to the highest BST_{max} for B7 at the end of charging, while the curves of the other four batteries nearly overlap during the whole charging process. As

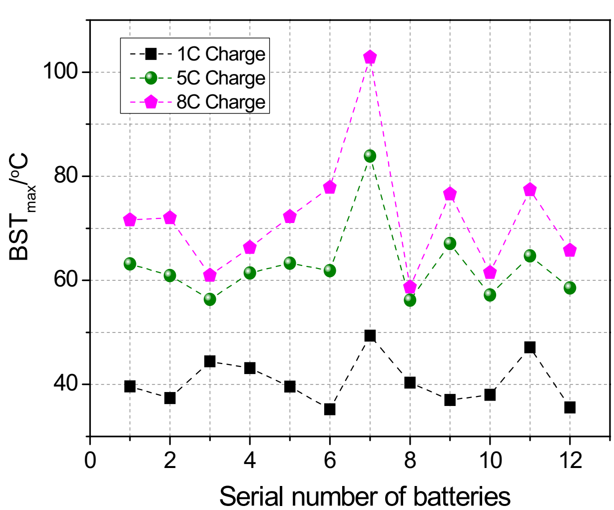

Fig. 3. The BST_{max} of batteries at the end of various charging.

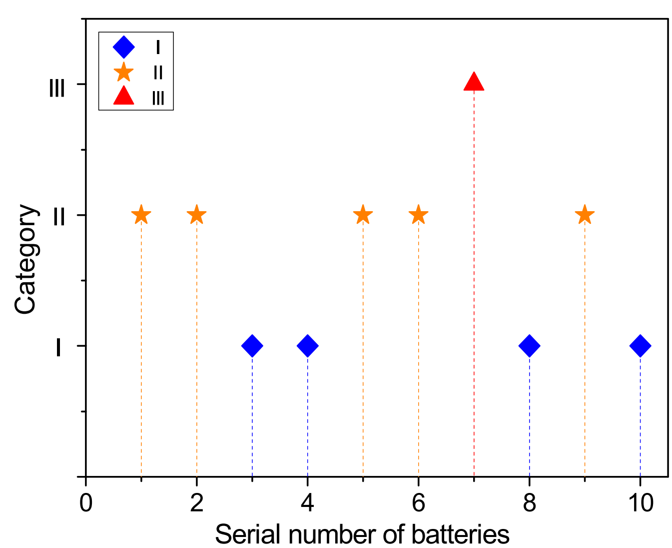

Fig. 5. The sorting result of ten batteries output by the model.

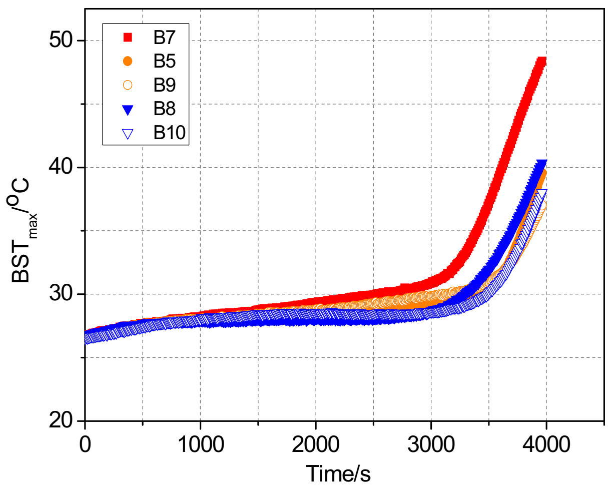

Fig. 6. The BST$_{max}$ rise curves of five batteries during charging, 1 C.

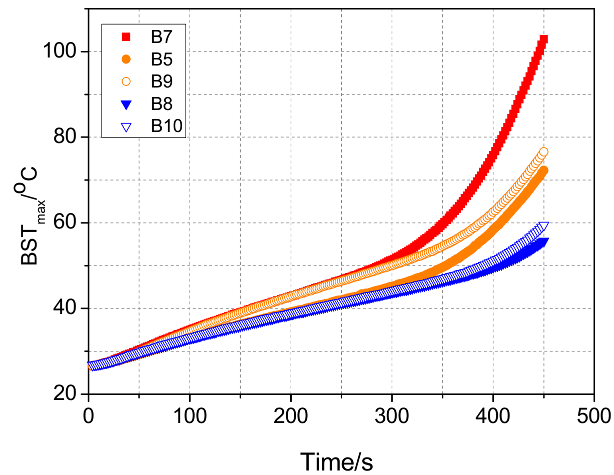

Fig. 8. The BST$_{max}$ rise curves of five batteries during charging, 8 C.

charging rates increase, the FRSs of the five curves in 5 C and 8 C charging become obviously distinguished as three categories, because the transit time of the MHB curves appear earlier than that of the LHB curves while the transit time for HHB is the earliest. Within the batteries sorted into the same category, thermal consistency is observed.

After being charged in various rates, the battery is discharged to 1.0 V in 1 C. The discharging curves are shown in Figs. 9–11, and the discharge capacities are listed in Table 1. In the case of 1 C charging, the discharge voltage platform (DVP) of every battery is almost the same, while the discharge time of B7 is less than that of the other fours. In the case of 5 C charging, the DVP of MHB drops down a little compared to LHB, and the discharging time of MHB reduces as well. Moreover, the distinction of discharge performance becomes much more obvious among the three categories of batteries when they are discharged after 8 C charging. In conclusion, LHB possesses the highest DVP and the longest discharging time among the three categories. As listed in Table 1, LHB also has the highest discharge capacity, the value of HHB is the lowest, while the capacity of MHB is just between the twos. This study thus demonstrated that the batteries sorted into the same category also maintain a consistency in discharge voltage platform and discharge capacity besides thermal consistency. This may be helpful to improve the electrochemical performance consistency of the batteries.

From the above analysis, it can be concluded that while working, HHB displays the highest surface temperature and the lowest

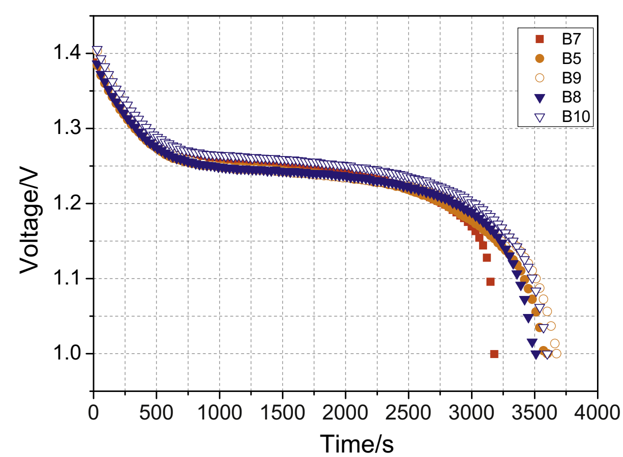

Fig. 9. The 1 C discharging curves of five batteries after 1 C charging.

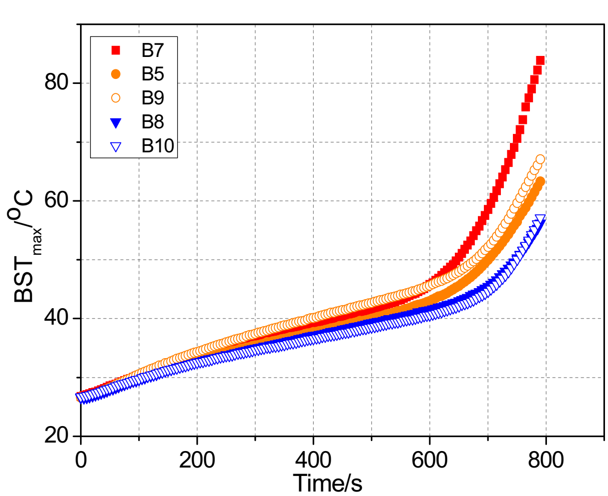

Fig. 7. The BST$_{max}$ rise curves of five batteries during charging, 5 C.

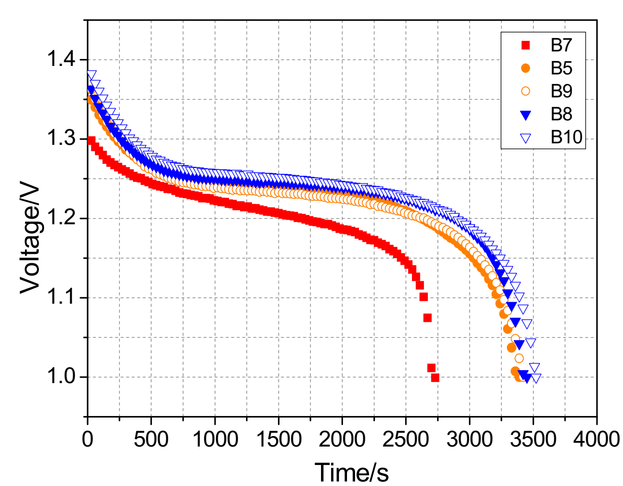

Fig. 10. The 1 C discharging curves of five batteries after 5 C charging.

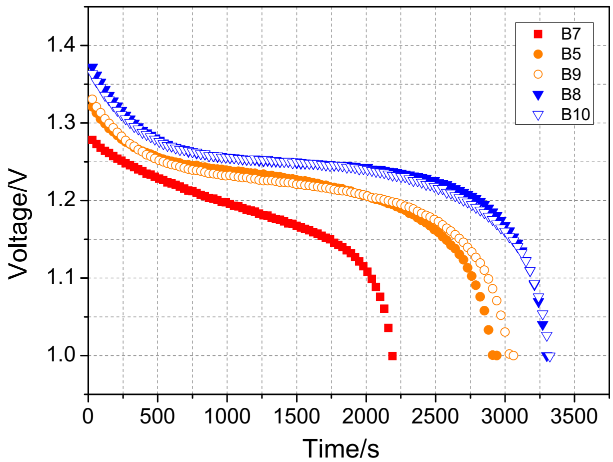

Fig. 11. The 1 C discharging curves of five batteries after 8 C charging.

Table 1
Discharge capacities of batteries in 1 C discharging after being charged in various rates.

	Discharge capacity [Ah]				
	B7	B5	B9	B8	B10
After 1 C charging	7.05	7.93	8.06	7.75	7.99
After 5 C charging	6.01	7.47	7.58	7.61	7.82
After 8 C charging	4.85	6.46	6.73	7.33	7.38

discharge capacity among the three categories of batteries. If HHB and LHB are used together in a battery pack, it is possible to cause serious thermal inconsistency. As a result, HHB will most likely tend towards thermal runaway under the same working condition, damaging the battery pack. Therefore, it is recommended to use the batteries of the same category to build a pack to ensure the consistency in thermal behavior and electrochemical performance, and the mixed use of batteries from various categories should be avoided.

5. Conclusions

An SOM model of ANN was constructed to sort Ni–MH batteries based on their thermal behavior during charging. They were effectively classified into three categories of HHB, MHB and LHB by this model. When sorted into the same category, the batteries displayed consistent thermal behavior as well as discharge performance. This work could thus assist to guarantee consistent performance of every battery within a pack.

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